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A neural network based operation guidance system for procedure presentation and operation validation in nuclear power plants

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Abstract

An operation guidance system (OGS) was developed to regulate and supervise operators' actions during abnormal environments in nuclear power plants (NPPs). The system integrated a primitive computerized procedures system (CPS) and an operation validation system (OVS) imbedded in a virtual simulated operational environment. As the key component of the OGS, OVS provided two important functions for the operators: validated check of operations, and qualitative and quantitative effects analysis of operations. Each of operators' action was evaluated by the system and possible results were simulated by using artificial neural networks (ANN). Finally, corresponding suggestion or warning was provided to operators. This should reduce human errors during operation in emergency scenarios.

1. Introduction

Nuclear power plants (NPPs) have special features, not only in the system's complexity, but also in the potential harmful results from control errors. Operator needs to use knowledge and experience to promptly and accurately assess and analyze current situations, and execute regular and suitable operations according to the operating procedures. The Three Mile Island (TMI) accident revealed that operators may not always adequately handle various and voluminous information, because high workload and stress would possibly make them fall into disorder. The importance of human factors in NPPs has been considered since the 1980s. A total of 180 significant events in NPPs have been reported in the United States, it was found that 48% of the incidents were attributed to human factor failures (Hwang and Hwang, 2003).

The recent development of information and ergonomic technology has accelerated the design innovation in NPPs. One of the potential areas for NPPs' innovation is how to involve the human factor in the system design, (i.e., how to reduce the human errors during operations). The traditional alarm analysis and operation modes during abnormal environments have been changed. More digitalized systems have been developed and installed in instrument and control (I&C) systems. Many operator support systems have been developed to help operators assess situations, present computerized procedures and regulate their operations according to current situations.

1.1. Computerized based procedures

In a conventional NPP main control room (MCR), operators handle, arrange, scan and read paper based procedures (PBPs) in parallel with monitoring and control tasks (Qin, 2004). PBP has drawbacks. PBP does not provide related information about the plant state. As a result, operators need to separately approach the control panel and plant state monitors. Since the PBP's content is written in a fixed format in natural language, the information may overwhelm operator. PBP is also heterogeneous and disintegrated in MCR environments with respect to future more advanced display and intelligent control systems.

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The development and implementation of computerized based procedure (CBP) began in the 1980s. COPMA-II was developed by the Halden Reactor Project in Norway (Jung et al., 2000). COMPRO was developed by Westinghouse Electric Corporation (Lipner and Kerch, 1994). CBP systems are currently used in many nuclear power plants (e.g., Beznau, Chooz B, Civaux, Temelin) (Chung et al., 2002).

The systemic and technical development of CBP needs to focus on technical and human factor requirements (Niwa et al., 1996). Most recent progress in CBP development is based on these requirements. Jung et al. (2000) developed a procedure building block by integrating decisions and responses to actions. Hwang and Hwang (2003) designed a computerized graphical interface based on dynamic work causality equation (DWCE) to transform the operating procedure into a flowchart. Some general rules for developing CPS have been summarized and demonstrated by Niwa and Hollnagel (2002).

1.2. Operation navigation and permission

The implementation of advanced display systems based on the large display panel and CRT based interface accelerates the information transfer between the plant and operators. However, the compacted screen and multi-windows software environments might assemble related information causing operator confusion, resulting in commission errors, especially in abnormal operations when a large amount of alarm information simultaneously appears. Only CPS is inadequate for avoiding human errors in these cases.

Gofuku et al. (2004a,b, 2005) developed a dynamic operation permission system using multi-level flow modeling (MFM) (Lind, 1994). The system was designed to prevent only evident commission errors and to allow operators do as they like as far as they follow operation manuals and various operational rules. MFM is a qualitative model, generating qualitative evaluations. In our proposed system, ANN was employed as the main algorithm for developing estimation functions. Because ANN is a quantitative model with strong fault tolerance ability, both qualitative estimation and more accurate quantitative results could be obtained.

1.3. ANN application in NPPs

Artificial intelligence (AI) methods, particularly neural ANN, fuzzy logic and genetic algorithms (GA) have been applied to the technical innovation of NPPs in last 20 years (Uhrig and Tsoukalas, 1999; Hines and Uhrig, 2005). With the strong fault tolerant ability to perform mathematical "mappings", ANN has been exploited in many applications in NPPs, including fault diagnostics (Reifman, 1997; Mol et al., 2003), signal prediction and validation (Fantoni and Mazzola, 1996; Uhrig and Tsoukalas, 1999), system control (Hwang, 1994), and diagnosis error estimation (Kim and Bartlett, 1994, 1996). ANN was developed for simulating the functions of human's neural system towards application to the computerized systems. It is composed of simple elements operating in parallel and the connections (weights) between them. ANN can be trained to perform a particular function by adjusting the values of the connection. A comprehensive study of ANN was published by Haykin (1994).

2. System design

The information processing model that describes the range of human activities required to respond to abnormal or emergency conditions involves four basic cognitive steps: monitoring/detection, situation assessment, response planning, and response implementation (US NRC, 1999). The major cognitive activities that underlie operator performance are shown in Fig. 1. Several functions for computerized supporting the activities of the model have been suggested by Lee and Seong (2005). Among these functions, OVS and CPS were proposed to support response planning. In response to abnormalities, operators need to perform four steps:

(1) Identify appropriate goals on the basis of their own situation assessment.
(2) Select appropriate procedure.
(3) Evaluate whether the procedure defined actions are sufficient to achieve those goals.
(4) If necessary adapt the procedure to the situation.

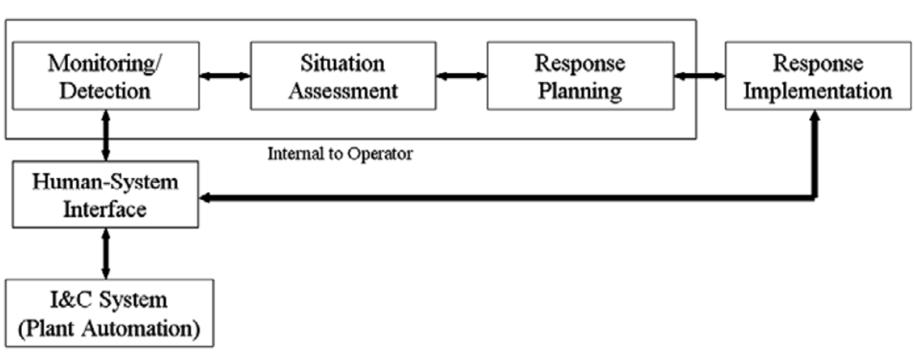


Fig. 1. Major cognitive activities underlying NPP operator performance.

Steps 1 and 2 can be partially assisted by CPS. However, for steps 3 and 4, CPS might be not helpful and thus OVS is needed.

2.1. System overview

The objective of this research is to develop a new integrated system covering computerized procedures presentation and operation validation. OGS includes two subsystems: CPS and OVS. The OGS was connected to a developed fault diagnostic system (FDS), which is for OGS initialization.

The basic system operating structure is shown in Fig. 2. The generated alarm signals were inputted into the FDS. By using ANN, FDS recognizes transient from known patterns in its database. After identifying the type of transient,

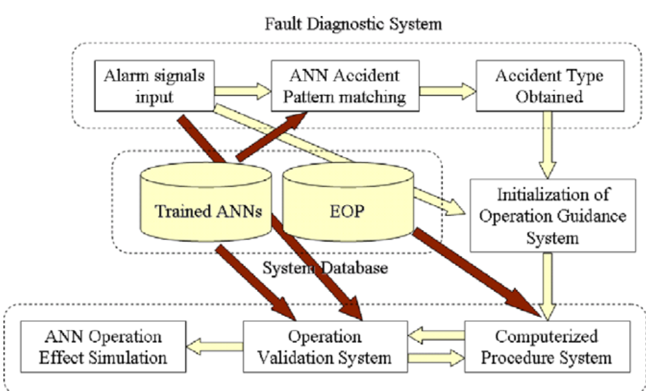


Fig. 2. System operation.

the OGS is initialized. Operators need to follow the guidance and procedures demonstrated by CPS to execute suitable operations. When operators try to perform an operation, OVS provides qualitative and quantitative effects analyses and provides a validated check. Operators choose to confirm or cancel their operations according to the evaluation results.

2.2. Computerized procedure system

The CPS is fundamentally built in the design of a prototype system. System procedures are separated by steps to reduce the magnitude of each information provision step. The inner relations among the procedures are expressed by such basic logic operators as AND, OR, IF, THEN, ELSE. Only two main panels were used for the interface design (Fig. 3). The left panel is used for presenting steps, which could be quickly and directly accessed by operators. The main panel in the middle of the screen is separated into two parts: the upper is for caution and the lower presents detailed procedures of each step. After CPS has started, the first step is shown. Operators need to follow the procedures and fill the checkboxes. In each step, if an operator does not fill some necessary checkboxes, he was not allowed to access to the next step.

2.3. Operation validation system

The objective of developing OVS is to provide an advisory system to supervise and validate the operator's actions during abnormal environments (i.e., to reduce operators' commission errors). The system imbedded in a virtual

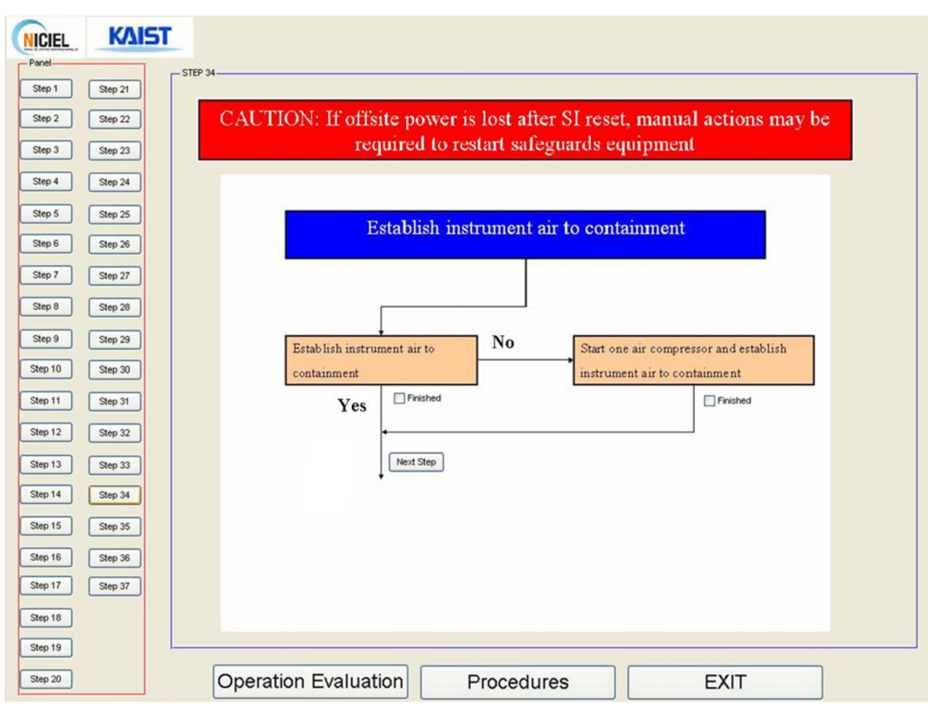


Fig. 3. Computerized procedure system.

simulated operational environment provides for operational validation and quantitative evaluations.

2.3.1. Simulated operational environment

All the necessary data was generated by compact nuclear simulator (CNS) (Kim et al., 1997; Kim and Seong, 2006; Mo et al., 2007; Lee et al., 1997) developed by Human System Interface Laboratory (HSIL). It was designed to carry out the various operational modes of a real nuclear power plant. It can be used for safety evaluations by transient analysis and testing fuzzy control algorithms, etc. (Park and Lee, 2001).

The reference plant is a standard three loop Westinghouse PWR. The generated data was stored in the system database. The virtual simulated operational environment was developed based on these data and ANN simulations. The windows of plant overview are shown in Fig. 4. The left panel is for presenting all controllable buttons in current operational environments. Besides the windows for plant overview, seven subsystems for control were also developed (Fig. 5). Thus, operators can conveniently choose the subsystem by pushing the "system selection" button. All the windows of plant overview and subsystems were developed based on the CNS's design. Operators can execute operations though the control buttons in the virtual environments.

2.3.2. Operational validation

The function of operational validation provides a checking mechanism for operators, in the case that they want to do some operations not included in the emergency operating procedures (EOP).

All operators' actions in simulated environment were classified into three levels according to their different potential threats (Fig. 6):

Level 1. The operations not permitted by plant's safety system: the operations were considered to be with strong potential threats to the safety of NPPs so that they were directly denied.

Level 2. The operations not included in EOP: the operations were considered to be inappropriate for current situations so that corresponding confirmations from operators were needed. Operators could choose to confirm or cancel their operations according to the possible results of the operation simulated by OVS.

Level 3. The necessary operations included in EOP: the operations were considered to be currently needed and directly permitted. Nevertheless, operators could still choose to validate the operation to check the possible influence of the operation.

All these permission selections were developed and stored in the system database which can be conveniently modified.

2.3.3. Qualitative and quantitative effects analysis of operations

OVS provides both qualitative and quantitative effects analysis of operators' action. They are used for different purposes: quantitative evaluations are shown simultaneously with the confirmation inquiry to operators. Operators can examine possible results of their expected

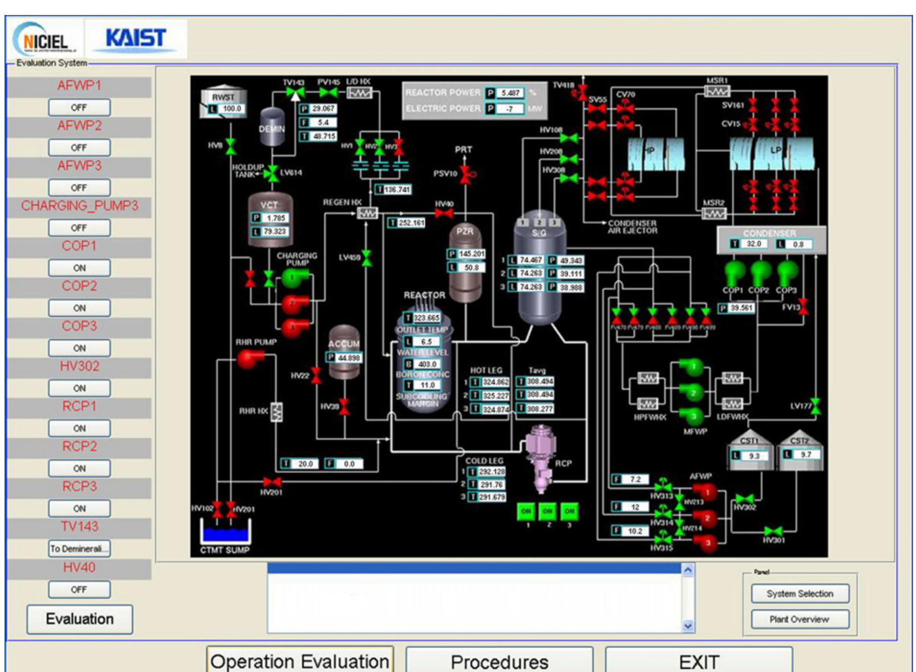


Fig. 4. Window of plant overview.

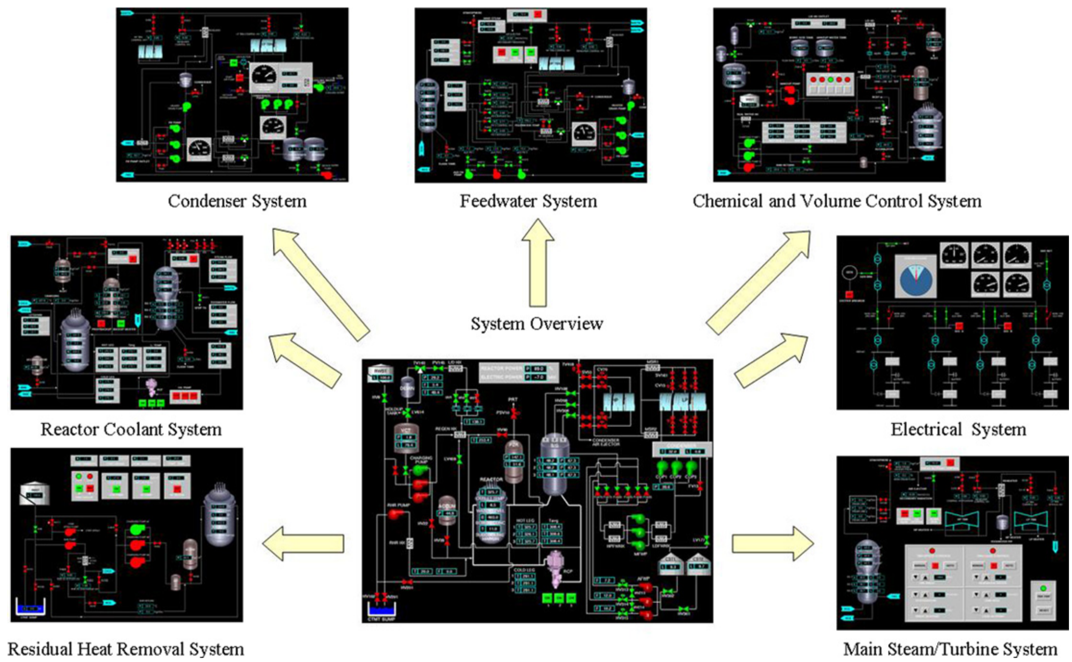


Fig. 5. Subsystems for control of simulated operational environment.

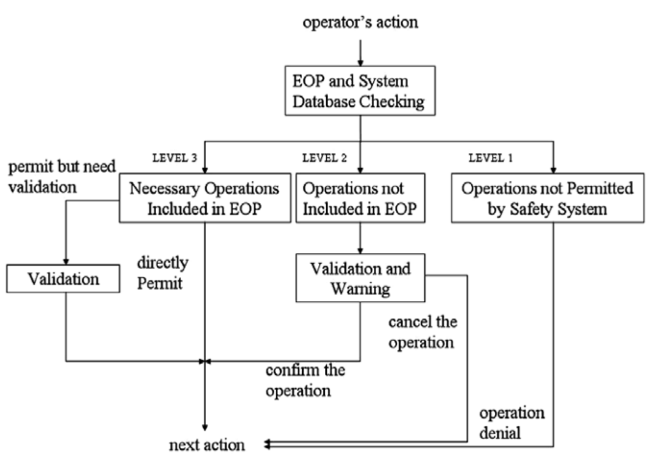


Fig. 6. Algorithm of operation validation.

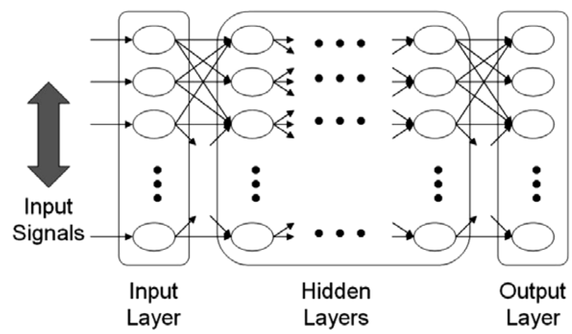


Fig. 7. Multi-layer perceptron.

operations and accordingly perform confirmation or cancellation. On the other hand, the quantitative evaluation provides more detailed information to operators. The trends of some key plant parameters under operators' action are generated. The quantitative evaluation is an optional function because the operator may not need to know the long time trend of specified plant parameters in order to make decisions.

2.3.4. System development and algorithm of analysis functions

2.3.4.1. Network training. Multi-layer perceptrons (MLPs) with resilient backpropagation algorithm were employed for system development (Fig. 7). The inputs of the neural networks constitute two kinds of data: plant status variables (Table 1) and control button status, while the outputs are the only plant status variables. Based on the maximum and minimum possible values of the variables, raw data obtained from the simulator were normalized to a continuous range from 0 to 1 before training. The normalization made the ANN learning easier, because the original input data contained both small and large scale.

Resilient backpropagation is a local adaptive learning strategy for weight-update of MLPs (Riedmiller and Braun, 1993). The resilient backpropagation' adaptation process is to eliminate the harmful effects of the size of the derivatives and use sign to determine the direction of update-weight. The working principles of algorithm are:

$$\Delta_{ij}^{(t)} = \begin{cases} \eta^{+} \times \Delta_{ij}^{(t-1)} & \text{if } \frac{\partial E^{(t-1)}}{\partial \omega_{ij}} \times \frac{\partial E^{(t)}}{\partial \omega_{ij}} > 0, \\ \eta^{-} \times \Delta_{ij}^{(t-1)} & \text{if } \frac{\partial E^{(t-1)}}{\partial \omega_{ij}} \times \frac{\partial E^{(t)}}{\partial \omega_{ij}} < 0, \\ \Delta_{ij}^{(t-1)} & \text{else,} \end{cases} \quad (1)$$

Table 1
Analog input description of the prototype

Reactor power	Pressurizer heater status
S/G Loop 1,2,3 steam flow rate	Accumulator flow rate
S/G Loop 1,2,3 feedwater flow rate	Safety injection flow rate
S/G Loop 1,2,3 wide range level	RHR pump rate
S/G Loop 1,2,3 narrow range level	Letdown flow rate
S/G 1,2,3 pressure	Charging flow rate
Containment pressure	Reactor level
RCS Loop 1,2,3 hot leg temperature	Turbine power
RCS Loop 1,2,3 cold leg temperature	Turbine steam flow rate
RHX output temperature	Turbine speed
RCS Loop 1,2,3 T_{avg}	Dump flow rate
RCS Loop 1,2,3 flow rate	Pressurizer saturation temperature
Pressurizer level	Pressurizer relief tank temperature
Pressurizer pressure	Pressurizer relief tank pressure
Pressurizer spray status	

where $\Delta_{ij}^{(t)}$ is an update-value for each weight (only for size); η^- and η^+ the increment fact, $0 < \eta^- < 1 < \eta^+$ and E the error function.

After obtaining $\Delta_{ij}^{(t)}$, the size of the update-weight $\Delta\omega_{ij}^{(t)}$ is determined. Its sign is determined by the partial derivative:

$$\Delta\omega_{ij}^{(t)} = \begin{cases} -\Delta_{ij}^{(t)} & \text{if } \frac{\partial E^{(t)}}{\partial \omega_{ij}} > 0, \\ +\Delta_{ij}^{(t)} & \text{if } \frac{\partial E^{(t)}}{\partial \omega_{ij}} < 0, \\ 0 & \text{else.} \end{cases} \tag{2}$$

However, if the partial derivative changed sign, the previous weight-update $\Delta\omega_{ij}^{(t-1)}$ should be reverted:

$$\Delta\omega_{ij}^{(t)} = -\Delta\omega_{ij}^{(t-1)} \quad \text{if } \frac{\partial E^{(t-1)}}{\partial \omega_{ij}} \times \frac{\partial E^{(t)}}{\partial \omega_{ij}} < 0. \tag{3}$$

After $\Delta\omega_{ij}^{(t)}$ was obtained, weight $\omega_{ij}^{(t)}$ could be updated:

$$\omega_{ij}^{(t+1)} = \omega_{ij}^{(t)} + \Delta\omega_{ij}^{(t)}. \tag{4}$$

Sigmoid function was used as the activation function in the system:

$$y_i = \frac{1}{1 + \exp(-v_i)}, \tag{5}$$

where v_i is the induced local field of neuron i and y_i the output of the neuron.

Various neural network training algorithms, including batch gradient descent, conjugate gradient algorithms and variable learning rate backpropagation, etc. have been tested with different terminating criteria and network size to obtain the optimal one. The inputs of the tests were selected transients from CNS database. The tests results were given in Table 2. All neural networks by different algorithms in the tests finally reach a certain mean-square-error. However, the training time and epoch by different algorithms showed considerable variability (Fig. 8). Resilient backpropagation had the best performance (Fig. 9), and thus was chosen for ANN training. The net-

Table 2
Tests of different training algorithms

Algorithms	Mean epochs	Mean time (s)
Basic backpropagation	3803.7	6.9323
Quasi-Newton algorithms (BFGS update)	101.39	68.7262
Quasi-Newton algorithms (one step secant algorithm)	360.36	1.5709
Conjugate gradient algorithms (Powell–Beale restarts)	185	0.9948
Conjugate gradient algorithms (Fletcher–Reeves update)	378.27	1.7023
Conjugate gradient algorithms (Polak–Ribiére update)	214.41	1.113
Gradient descent backpropagation	17,765	31.8003
Conjugate gradient algorithms (scaled conjugate gradient)	199.13	0.9100
Variable learning rate	10,897	20.0898
Variable learning rate with momentum training	3140.5	5.8788
Levenberg–Marquardt algorithm	8.87	8.6605
Resilient backpropagation	218.31	0.5678

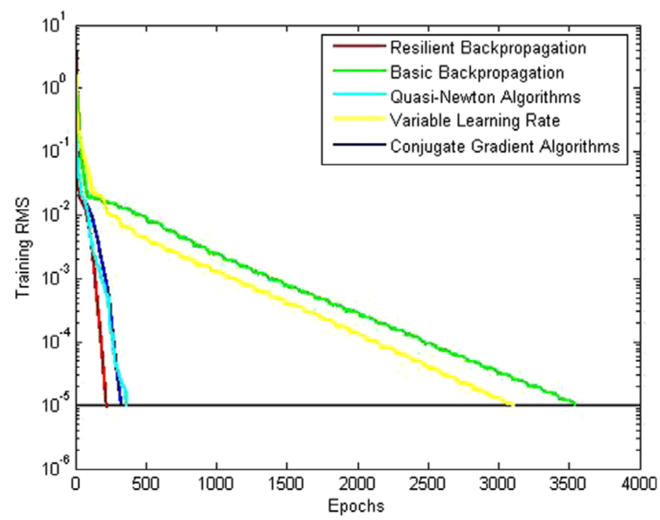


Fig. 8. Learning curve for selected competing algorithms.

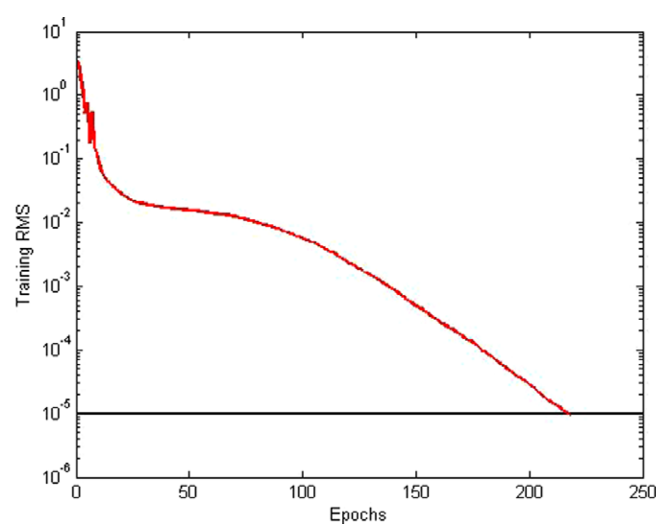


Fig. 9. RMS error performance for RPROP network.

Table 3
Type of the transients

Loss of coolant accident (LOCA)
Feedwater line break (FLB)
Steam generator tube rupture (SGTR)
Steam line rupture (SLR)
Reactor coolant pump stop transients
Failure in PRZ pressure controller
Reactor coolant pump trip
Loss of charging pump
Turbine trip
FW pump trip

works with two hidden layers consisting of 20 nodes of each provided reliable and fast resilient backpropagation training in processing the large amount of time-series data and thus were chosen for system development.

Ten types of the transients have been extracted from CNS into system database (Table 3). More types of transients would be included in system database in future system update. After training, the ANNs were stored by types in the database and only will be selected to use when it obtained the information from the FDS.

2.3.4.2. Ports between FDS. An FDS based on a dynamic neural network aggregation (DNNA) model was developed in previous research (Mo, 2006; Mo et al., 2007). The system provides comparatively accurate information about transients' type, severity and location to operators. This information is used as a reference for choosing trained ANNs from the database. After the specified ANNs were selected, the initialization for running the OVS was finished.

2.3.4.3. Result generation. The main algorithm for system operation is shown in Fig. 10. After system initialization was finished, the current plant status parameters are imported to the system. Parameters are first normalized and inputted to the input layer of the trained ANN. The operational results are calculated according to the operator's action. The time for generating qualitative report and quantitative evaluation is different. For the qualitative report, only one ANN ($T = 200$ s) is used, thus the time for calculation is nearly negligible. For the quantitative evaluation, much more ANNs ($T =$ current time $+ 1$ s to $T =$ current time $+ 200$ s) are used and the results are incorporated from all the outputs. Therefore, the time for calculation is much more than the one for generating qualitative report. Hence, the quantitative evaluation is developed as an optional function for operator's reference.

After the outputs of ANNs were generated, some parameters with largest change by the actions are selected for demonstration. The parameter selection factor S_i was defined to represent the magnitude of the change of parameter i after operation:

$$S_i = \frac{Y_i^c - Y_i^o}{Y_i^o} \tag{6}$$

where Y_i^c is the changed value of parameter i; Y_i^o the original value of parameter i.

S_0 is the limit value of S_i for qualitative report:

If $S_i > S_0$, the changed value was considered to be increased.
If $S_i < -S_0$, the changed value was considered to be decreased.
If $|S_i| \leqslant S_0$, the changed value was considered to be changed little.

Eight plant status parameters with large $|S_i|$ were selected for qualitative report and quantitative evaluation. There was one exception: If less than five parameters meet the condition $S_i > |S_0|$ (i.e., most of plant status parameters

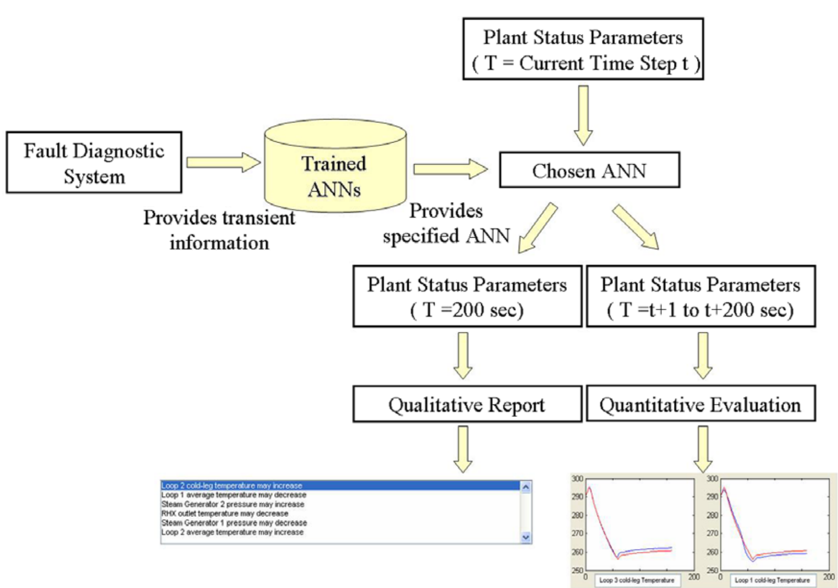
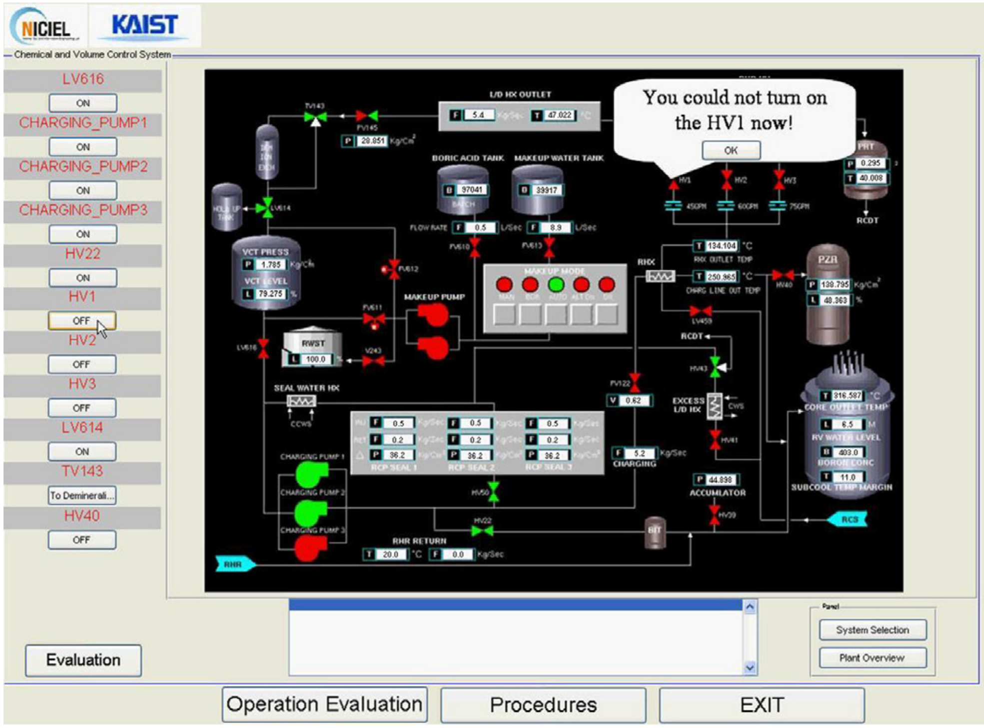


Fig. 10. Operation of analysis function.



Operation direct denial

Fig. 11. Example 1. Turning on HV1.

do not have a significant change), only five of them would be demonstrated because influence of the action was not considered to be important.

The most suitable value for S_0, found experimentally, was 0.01.

3. Operational examples

Three examples of operations were demonstrated according to different warning levels in order to clearly illustrate the system operation. The operational environment was simulated at the moment just after the reactor trip of a small LOCA.

3.1. Manually opening the HV1 in chemical and volume control system (Level 1)

The system operation for operators turning on the HV1 in Chemical and the Volume Control System (CVCS) of the simulated operational environment is shown in Fig. 11. Because HV1 was considered to be improper to be opened since the action would threaten the system safety, OVS directly rejected this operation.

3.2. Manually shutting down the reactor coolant pump 1 in reactor coolant system (Level 2)

The system operation for operators shutting down the reactor coolant pump 1 (RCP1) in the reactor coolant system (RCS) of the simulated operational environment is shown in Fig. 12. The qualitative report shows that the temperature of loop2 and loop3 was increased, while the temperature of loop1 was decreased. From quantitative evaluation, as expected, the temperature was firstly found to dramatically increase because of shutting down of RCP and finally decrease because of safety injection. (The red curve[1] in the figure shows an original trend without any action, while the blue one shows the changed trend after RCP1 is turned off.)

Because RCP1 was considered to be improper to be shut down according to the EOP, the system automatically provided a qualitative report to operators and asked for confirmation. Operators can choose to confirm his action or further refer to the quantitative evaluation.

3.3. Manually opening the auxiliary feedwater pump in system overview window (Level 3)

The system operation for operators opening the auxiliary feedwater pump (AFWP) in system overview window of the simulated operational environment is shown in Fig. 13. The qualitative report shows that the plant status parameters have no significant change. From quantitative evaluation, as expected, the changed and original curves of all shown parameters nearly overlap.

Because this operation was included in EOP and considered to be necessary for the current environment, the sys-

[1] For interpretation of colour, the reader is referred to the web version of this article.

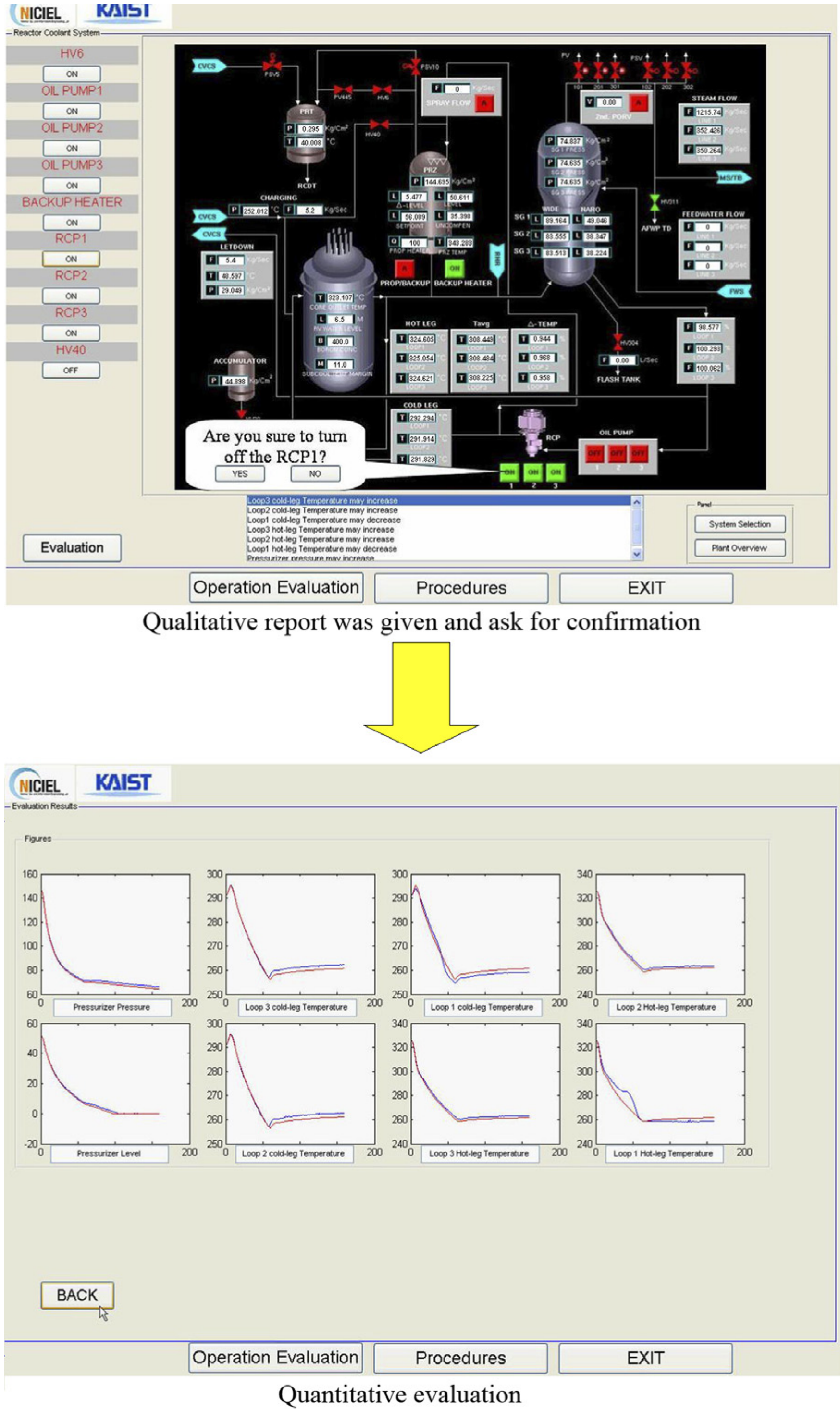


Fig. 12. Example 2. Shutting down RCP 1.

tem directly permitted the operation. Operators could still access a qualitative report or quantitative evaluation for the situation understanding.

4. Discussion

Because of the difficulty in obtaining real data from NPPs, most of the current research of OSSs development used generated data from the simulator (US NRC, 2003). Embrechts and Benedek (2004) gave a comparison of data from the plant and simulator to prove that the data was useful for experimental system development.

MLPs have been applied successfully to solve some difficult and diverse problems in a supervised manner using various learning algorithms. MLPs need comparatively less time for calculation with strong fault tolerance ability. The

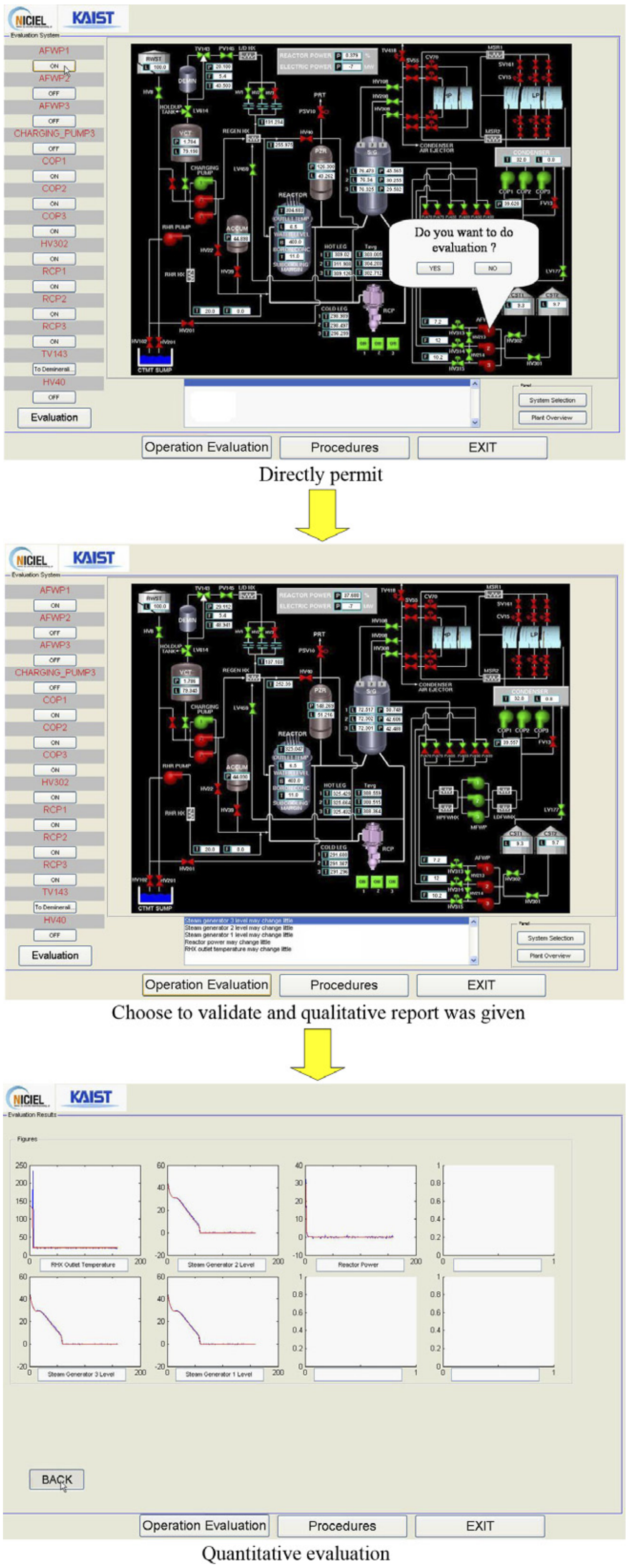


Fig. 13. Example 3. Turning on AFWP.

time for estimation of influence of operators' action is key factor for system development since the system's function is to provide operational evaluation during emergency. Therefore, although a simulator based on the physical functions could generate more accurate estimation, it is not suitable because it will take much longer time (Gofuku et al., 2005).

The simple CPS was developed only for procedures presentation as the base for OVS. It can be replaced by other advanced designed CPS, such as ImPRO developed by Jung et al. (2000).

Since the FDS is the prior system of OVS, The accuracy of OVS is strongly related to the FDS (i.e., if FDS could not provide correct type of the transient, then OVS's results would be incorrect). The analysis of the reliability of the system should be further studied.

5. Conclusion

In this study, a new operator support system for operation guidance in emergency of NPPs has been developed. The system consists of two subsystems: CPS for procedure presentation and OVS for operation validation. The CPS was early developed as the base for OVS. OVS provides two important functions for operators: validated check of operations, and qualitative and quantitative effects analysis of operations. The MLPs type neural networks trained by "Resilient Backpropagation" algorithms were stored in the system database and approached by OVS when operators perform specific actions.

Human errors, including omission errors and commission errors, significantly threaten the safety of NPPs, especially in abnormal environments that suitable actions to assess and relieve the situation must be performed by operators. CPS provides a checking scheme so that operators' omission errors can be considerably reduced. OVS provides an additional function for the control panel to supervise and validate operator's actions. Thus, the operators' commission errors should be effectively reduced.

Acknowledgements

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